

EXTENDED ABSTRACT

Adaptive Interplanetary Navigation using Genetic Algorithms

Todd A. Ely
MS 301-125L
Jet Propulsion Laboratory
California Institute of Technology
4800 Oak Grove Drive
Pasadena, CA 91109-8099

Phone: 818-393-1744
Email: Todd.A.Ely@jpl.nasa.gov

Robert H. Bishop and Timothy P. Crain
Mail Code C0600
Department of Aerospace Engineering and Engineering Mechanics
The University of Texas at Austin
Austin, TX 78712-1085

Phone: 512-471-4258 (Bishop)
512-471-3681 (Crain)
Email: bishop@csr.utexas.edu
crain@csr.utexas.edu

Prepared for the
Richard H. Battin Astrodynamics Symposium
Reed Arena, Texas A&M University
College Station, Texas

March 20 – March 21, 2000

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T. A. Ely, R. H. Bishop, and T. P. Crain

The problem of tuning trajectory determination models for interplanetary navigation is a complex task requiring an intensive search of multiple dynamical and nondynamical models to find an optimal solution. The process that operational teams currently utilize is based as much on previous experience, as it is on a scientific understanding of these underlying models. Furthermore, there is an ever-increasing demand for navigation analysts to support multiple spacecraft missions (each with unique modeling issues) using tools that have inherent limitations because of the generic models utilized by these tools. As an example, the Mars Pathfinder (MPF) spacecraft that successfully landed on Mars in July 1997 had a backshell shroud that protected the lander during cruise and Mars entry. It was conical in shape and, during the cruise phase, often shadowed from the Sun by the spacecraft solar arrays. However, the component models available for use by the MPF analysts for solar radiation pressure modeling consisted of only flat plates and cylinders. Neither was entirely correct, thus they were forced to approximate the model of the backshell using one of these choices with an unknown scale factor (because of shadowing) [1]. Their approach was iterative requiring the team to select a model, adjust the filter realization, process the observations, and then compare results to previous filter realizations. Clearly, this tuning process could have benefited from a systematic and automated methodology for finding a best filter model. Doing so would ease operation team workloads and allow them to consider a wider range of possible solutions. This study presents a method for adaptation of navigation models using genetic algorithms to search a selected design space, and arrive at a model that best fits the measured spacecraft tracking data.

Popular approaches to model adaptation often utilize parallel filter banks, each operating with different internal model realizations. The Magill filter bank is a classic method utilizing a Bayesian method to assign probabilities to each member of the bank, with the aggregate of the bank forming an 'optimal' output. Unfortunately, this method, along with others, suffers from the fact that only a small portion of a potential modeling space can be considered in any given realization of a filter bank. Additionally, the Magill filter experiences numerical underflow problems for long spans of data [2],[3]. Early attempts to utilize Magill filter banks for interplanetary orbit determination were reported by Burkhart and Bishop [4]. Another classical technique accommodates modeling errors by matching process noise and measurement noise statistics to the received data [5]. A recent application of this approach by Powell [6] successfully utilizes a simplex method, and thus does not require gradient information about the filter. These methods maintain tracking stability of the filter, however they do not address the fundamental issue of adjusting internal modeling assumptions that may have become suboptimal. Many other model optimization techniques exist, such as the recursive quadratic programming (RQP) approach investigated by Chaer, Bishop, and Ghosh [3],[7], however they are typically based on the existence of gradient information. These do not exist when considering model changes between discrete options (i.e., such as changing a flat plate to a cylinder). Adaptation using genetic algorithms (GA) is ideally suited for situations where the design space is complex and consists of mixed variable (discrete and continuous) because GAs do not require gradient information. However, currently, they are not well suited for real time processing because their convergence is evolutionary in nature. Nevertheless, interplanetary navigation (especially during cruise) is typically a process that operates on spans of data that are days to weeks in length, and the filter tuning process (via analysis by a navigation team) can take many days as well. Thus, use of a genetic algorithm to assist in this process is warranted. Previously, Chaer, Bishop, and Ghosh [3], [7], and Chaer and Bishop [8] employed GAs for adaptive orbit determination during interplanetary cruise, however, their efforts focused on adjusting internal parameters (e.g. measurement and process noise) within individual filters of fixed structure. Using gating networks to regulate the filter bank, the GA operated in an outer loop with the performance of the individual filters represented by the gating network weights. In this new application, the GAs are used to adapt the individual filter structure by effectively updating the spacecraft model itself. The filter bank is utilized as the GA population. This is a significantly different application of the GAs from previously reported investigations. Also, for the first time, actual DSN tracking data is used in the investigations, whereas previous studies relied on simulated DSN tracking data.

The current study employs a GA coupled with an extended Kalman filter (EKF) for model optimization. In particular, the solar radiation pressure (SRP) model of the Mars Pathfinder spacecraft is investigated using a 2½ month span of tracking data during the cruise phase of the mission. The results obtained in this study are compared

to the best model obtained by the MPF navigation team. During operations the issue of appropriate component models was of a central concern. Shadowing of the backshell, coupled with a limited component selection complicated the team's search for an appropriate model. Given this experience, the design space selected for the GA search includes component selection of the backshell between either cylinders or flat plates. The size and orientation of these components is selectable. The GA design space also includes as selectable parameters the apriori covariances for the SRP component area scale factors. The GA operates on a population of individuals that are selected (initially at random) from this design space. Each individual processes the tracking data set via the EKF. The basis for the GA's fitness function is a normalized sample statistic of the output innovation sequence for each individual. Using the fitness values computed for each individual, the GA selects the parent population via a tournament method. For crossover, several strategies are investigated to determine the best method for quick convergence of the GA to a near optimal solution. The selected design space includes $1.44\text{E}+17$ distinct SRP models, and the results show that the GA is able to determine an SRP model with a fitness value that is 10% better than the model selected by the MPF navigation team.

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